Original fairness Slides

AI Ethics

CS229: Machine Learning

Carlos Guestrin
Stanford University

The Ethics of AI

- Thus far, we focused on methods and techniques

- But, the systems we build impact people, everyday
- The ethics of AI focuses on the principles and methods to help ensure our systems reflect our values
  - There are social, political and legal implications
    - But, we'll focus on methods for the next two lectures
- Much more too learn
  - See CS281 – Ethics of AI in Spring 2022

Are Emily and Greg More Employable than Lakisha and Jamal? [Bertrand & Mullainathan '03]

ML-based system for recruiting

- Could decrease this bias…

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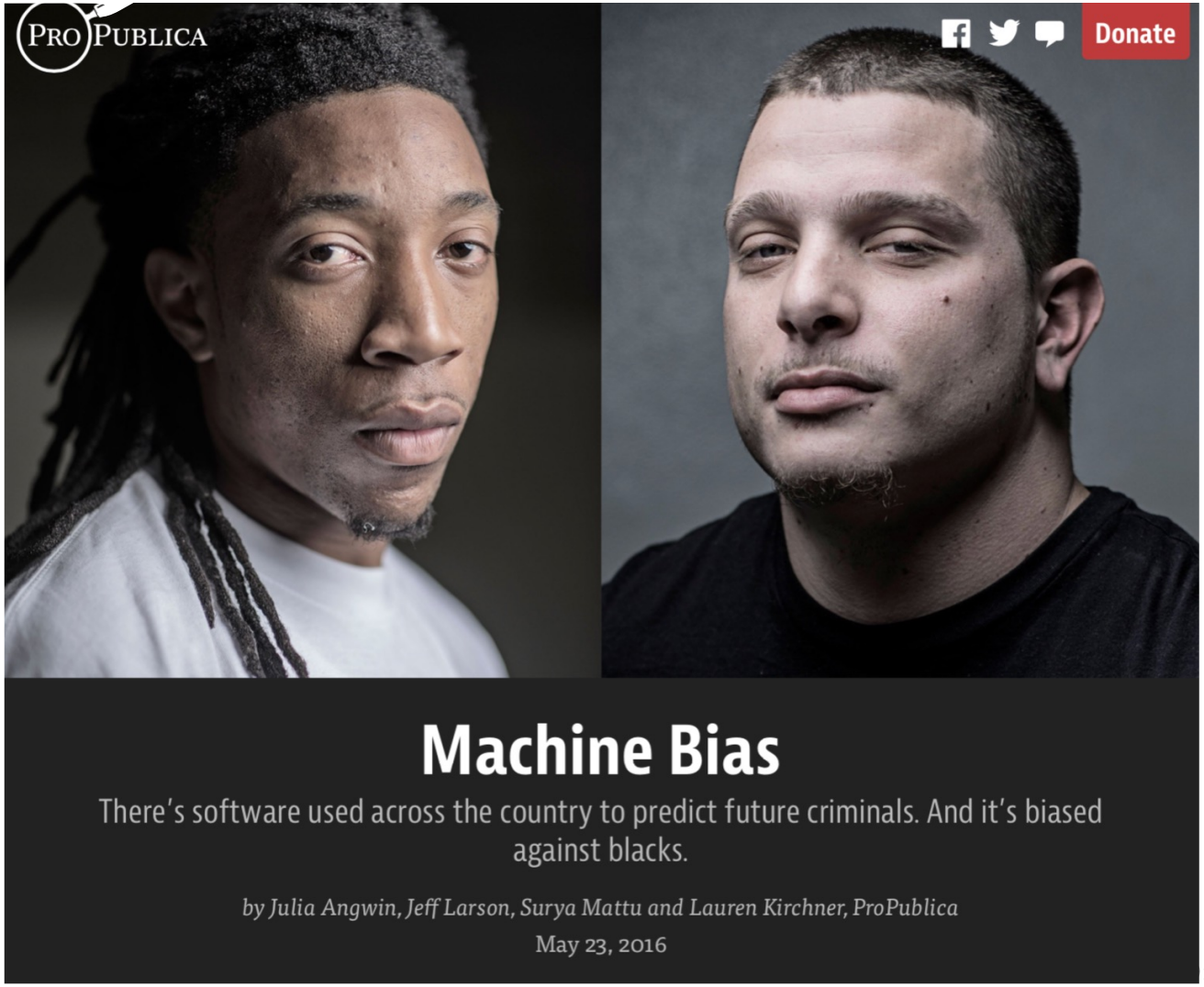
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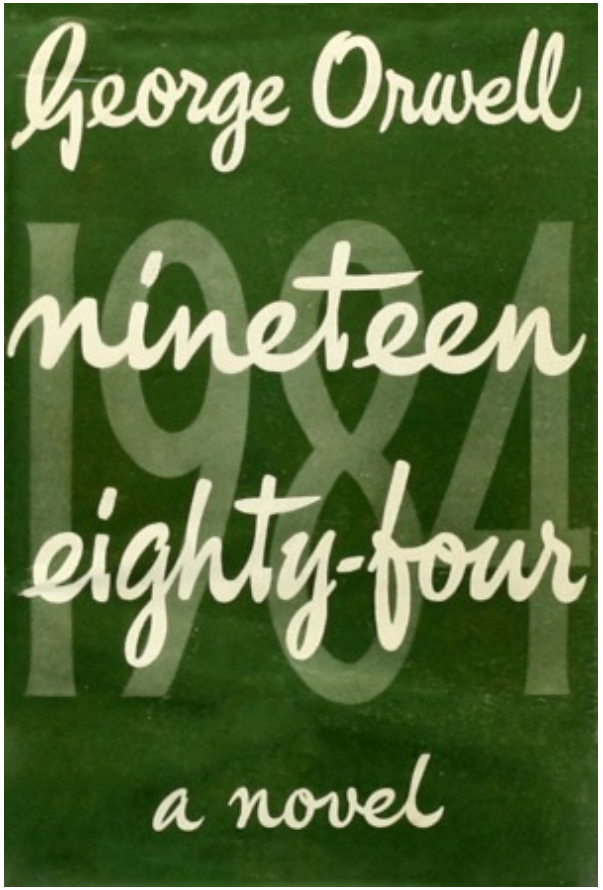

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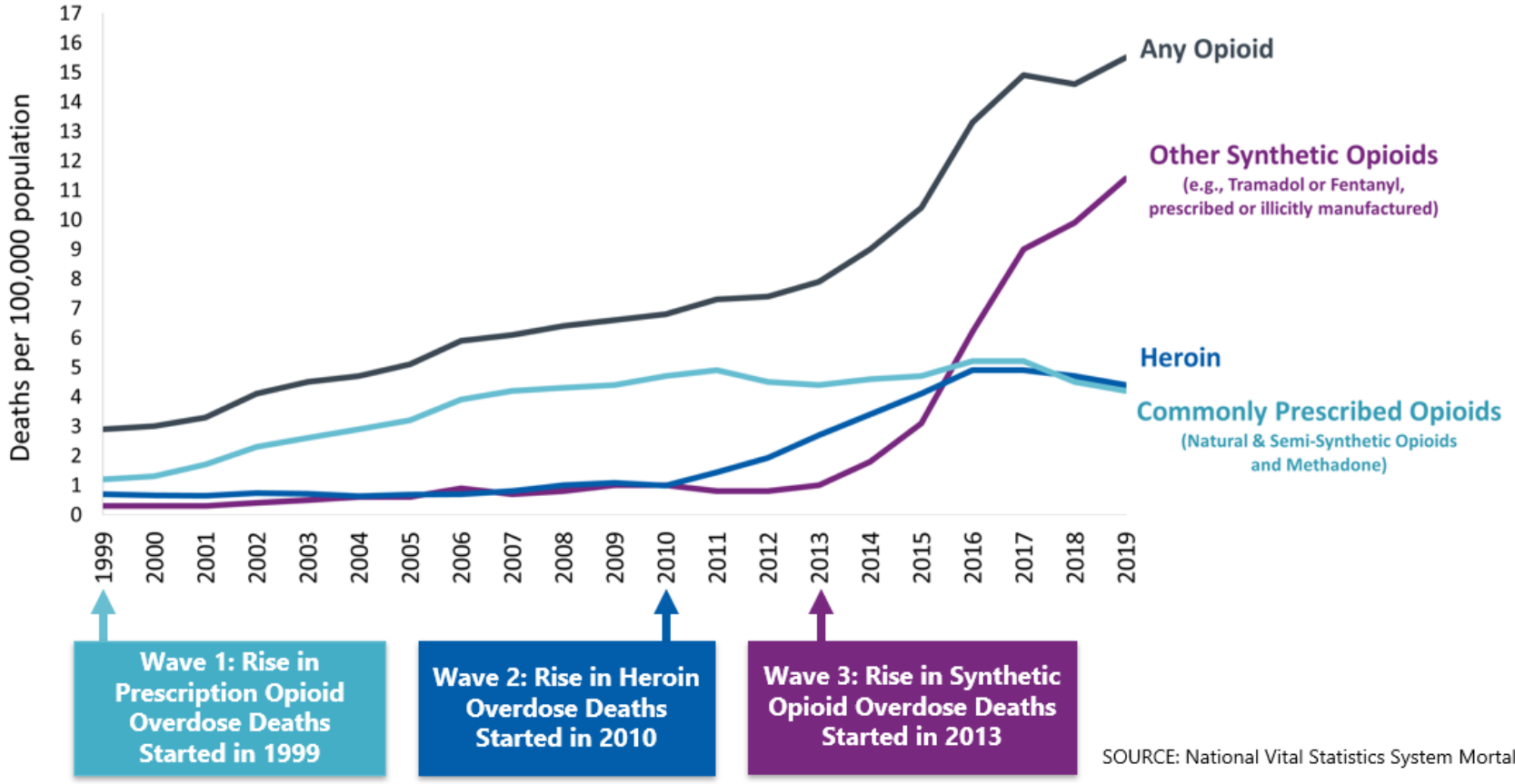

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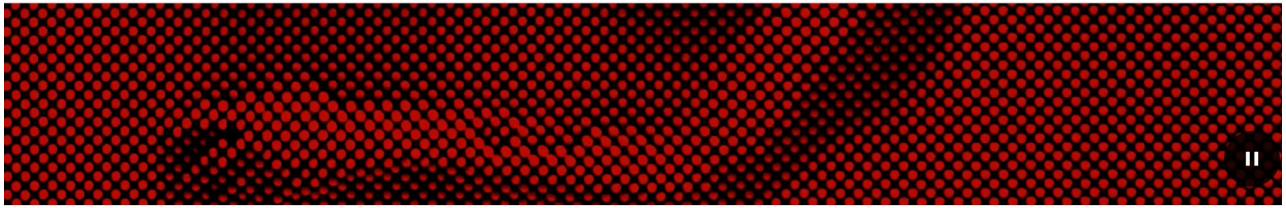

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The Pain Was Unbearable. So Why Did Doctors Turn Her Away?

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APPLICATION: ETHICS, PREDICTION, REGULATION

SECTOR: HEALTH CARE, PUBLIC SAFETY

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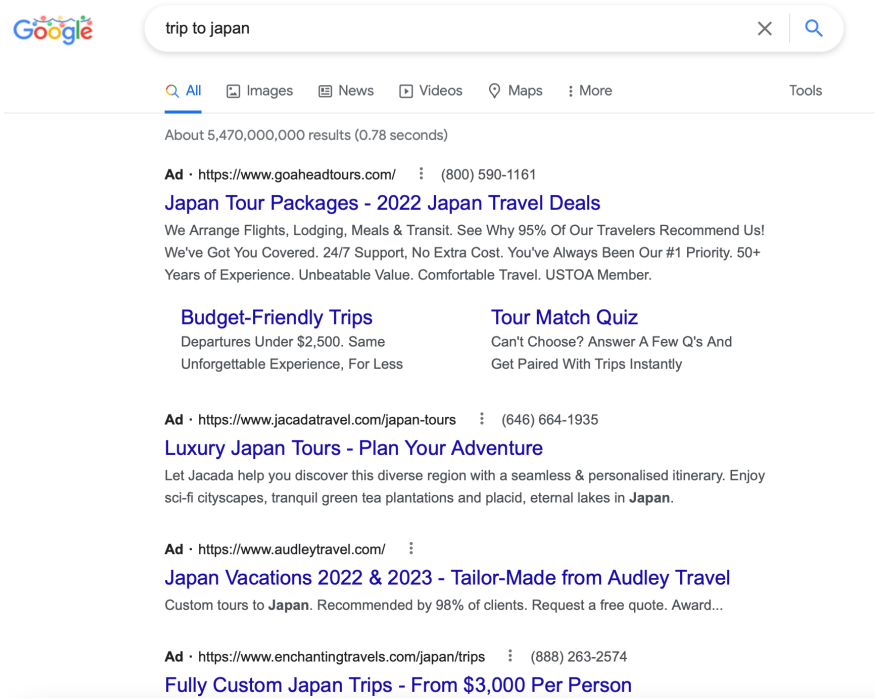
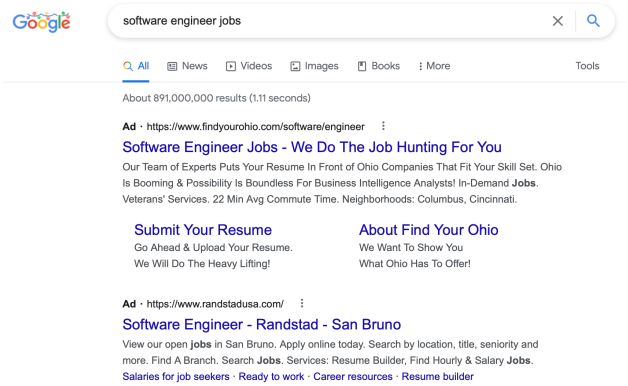
Biased Decisions

Ads can be annoying…



Ads can represent opportunity…



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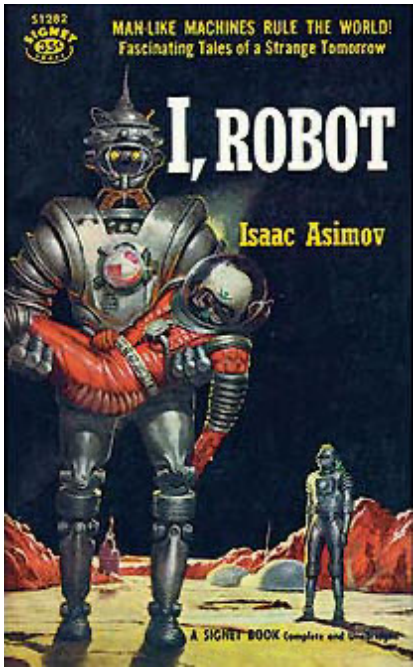

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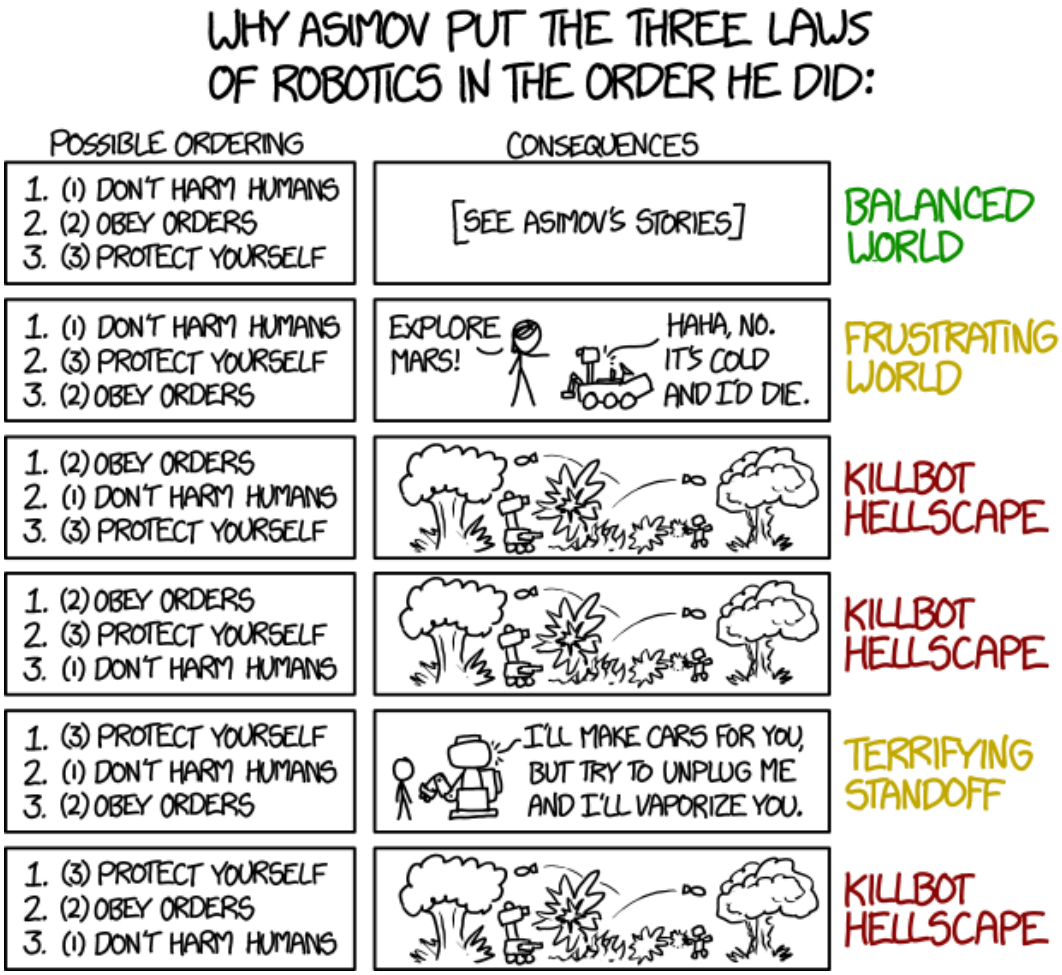

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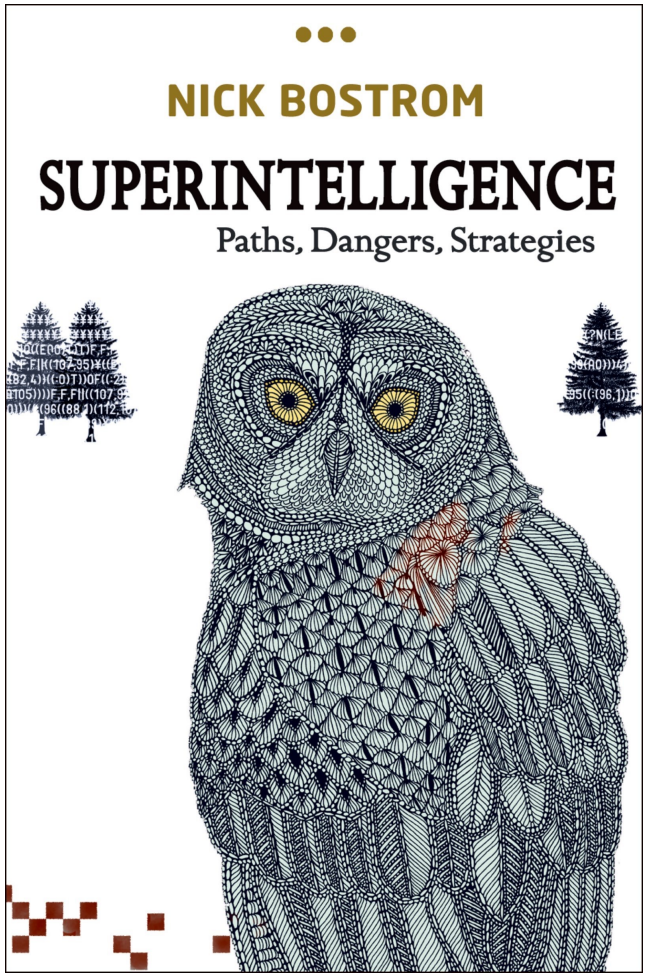

Focus of Next 2 Lectures

- Fairness and algorithmic bias
- Explainability
- Privacy

AI Ethics:
Fairness & Algorithmic Bias

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Regulated Domains

- **Credit** (Equal Credit Opportunity Act)
- **Education** (Civil Rights Act of 1964; Education Amendments of 1972)
- **Employment** (Civil Rights Act of 1964)
- **Housing** (Fair Housing Act)
- **'Public Accommodation'** (Civil Rights Act of 1964)

Legally-Recognized Protected Classes in the US

Race (Civil Rights Act of 1964); **Color** (Civil Rights Act of 1964); **Sex** (Equal Pay Act of 1963; Civil Rights Act of 1964); **Religion** (Civil Rights Act of 1964);**National origin** (Civil Rights Act of 1964); **Citizenship** (Immigration Reform and Control Act); **Age** (Age Discrimination in Employment Act of 1967);**Pregnancy** (Pregnancy Discrimination Act); **Familial status** (Civil Rights Act of 1968); **Disability status** (Rehabilitation Act of 1973; Americans with Disabilities Act of 1990); **Veteran status** (Vietnam Era Veterans' Readjustment Assistance Act of 1974; Uniformed Services Employment and Reemployment Rights Act); **Genetic information** (Genetic Information Nondiscrimination Act)

Sources of Bias

Sources of Bias: Human Bias

- Data reflects human decisions and biases
- Example: ML for Hiring decisions
  - Data from previous hiring decisions perpetuates existing biases
  - Could reduce bias by measuring employee success
    - Harder to measure and institutional biases can impact success

Sources of Bias: Negative Feedback Loops

- Data collected in biased fashion
  - Negative feedback loop: future observations confirm predictions and reduce further contradicting evidence
- Example: Allocation of police attention based on prevalence of crime

Sources of Bias: Sample Size Disparity

- Models for minority group may be less accurate, if less data is used
- Example: Race representation in medical studies

Sources of Bias: Unreliable Data

- If data from minority groups is less reliable or less informative
  - Models may be less accurate for minority groups
  - (Beneficial) interventions may less available to minority groups
- Examples:
  - Inaccurate census in predominantly minority neighborhoods
  - Medical interventions with limited diagnostic tools

Sources of Bias: Proxies

- Even if sensitive attributes (e.g., gender or race) are not used by model, there may be other proxy features that are correlated with sensitive attributes
- Example: Redlining in loan and insurance applications
  - https://www.npr.org/sections/thetwo-way/2016/10/19/498536077/interactive-redlining-map-zooms-in-on-americas-history-of-discrimination
  - https://www.npr.org/2017/05/03/526655831/a-forgotten-history-of-how-the-u-s-government-segregated-america

Mitigating Bias at Every Stage

- Problem definition
- Data collection
- Model development
- Model evaluation
- Use of predictions in practice
- Feedback loops

How do we measure fairness?

Consider a loan application…

- **x** – features of applicant (address, credit history,…)
- **c** – sensitive features of applicant (gender, race,…)
- d – decision (loan approved or denied)
- y – (hidden) true target in decision (will this person pay the loan)

- Shorthand probability notation:

- "Perfect" predictor:

Fairness through Unawareness

- Definition:

- Desirable properties:

- Criticisms:

Three Important Fairness Criteria

- Independence
- Separation
- Sufficiency

All these criteria are achievable…

- Techniques include:
  - Pre-processing
  - Changing training procedure
  - Post-processing

1. Independence

- Definition: Decision d independent of sensitive features **c**

- A.k.a. **demographic parity**: Probability of loan approved is the same across sensitive attributes

Independence: Desirable Properties

- Simple
- Some legal support
- In some settings, can increase representation, e.g., in admissions

Independence: Shortcomings

- Ignores possible correlations between y and **c**
  - Precludes perfect predictor d=y

- Laziness: quality of decision doesn't need to be uniformly good between groups

2. Separation

- Definition: decision d and sensitive features **c** conditionally independent given true target y

Variant of Separation: False negative rate parity

- Probability of loan denied for a deserving applicant is the same across sensitive attributes

Separation: Confusion Matrix Interpretation (Equalized Odds, Equal Opportunity)

- Separation:
- Confusion matrix:
- Variants:

Separation: Desirable Properties

- Optimality compatibility

- Incentivize to reduce errors equally across groups

Separation: Shortcomings

- Can amplify disparities

3. Sufficiency

- Definition: decision variable d is sufficient to predict target y, independently of sensitive features **c**

- Equivalently, predictive rate parity:
  - Positive predictive rate:
  - Negative predictive rate:

Sufficiency: Desirable Properties

- Optimality compatibility:

- Equal chance of success, given acceptance:

Sufficiency: Shortcomings

- Also can amplify disparities

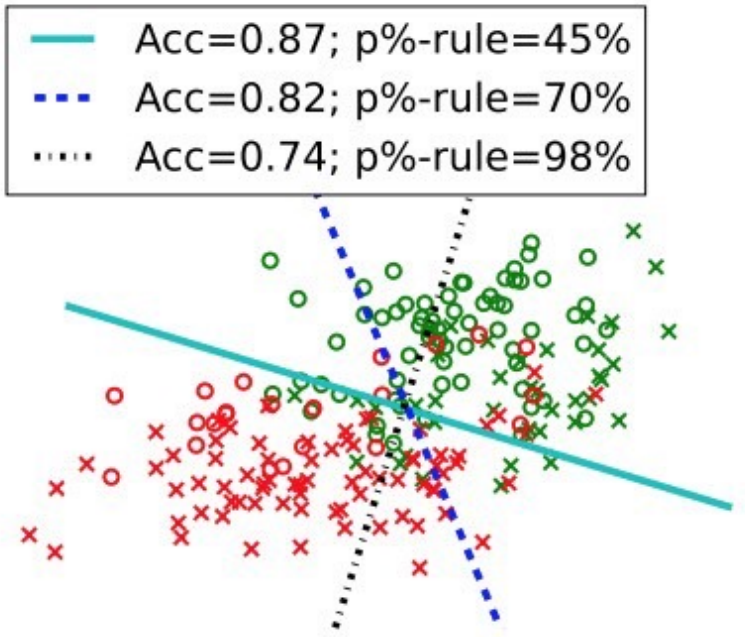
All these criteria are achievable…

- Techniques include:
  - Pre-processing
  - Changing training procedure
  - Post-processing

Trade-offs are Inevitable

Tradeoff Between Fairness and Accuracy

Tradeoff Between Group-Specific Performance and Average-Case Performance



Accuracy vs demographic parity [Zafar et al. AISTATS2017]

Impossibility Result

- Independence, Separation & Sufficiency are reasonable criteria
- **Theorem**: Any two of these is mutually exclusive!!
  - Except for degenerate cases

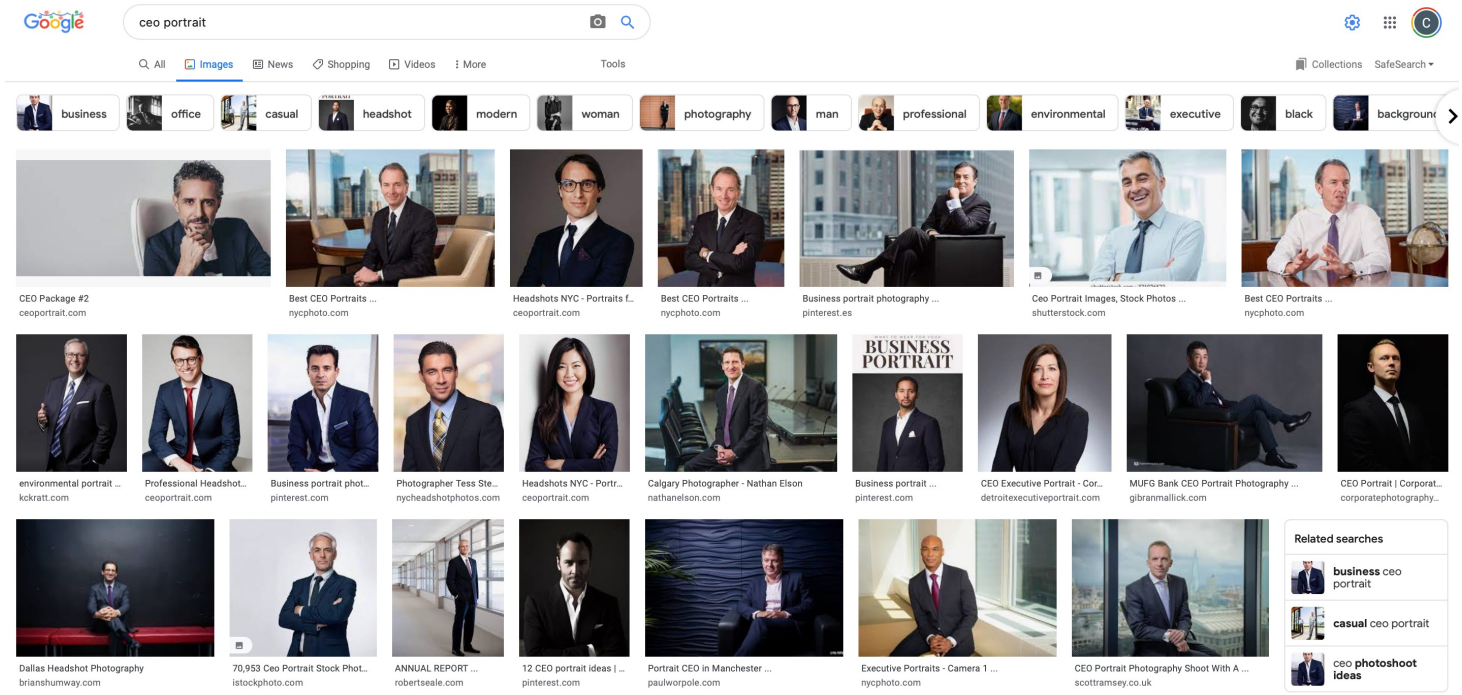
Trade-offs are necessary!

- Choose a criteria, instead of others?
  - Which one?
- Choose a balance between criteria?

- Very general issue in fairness and ML

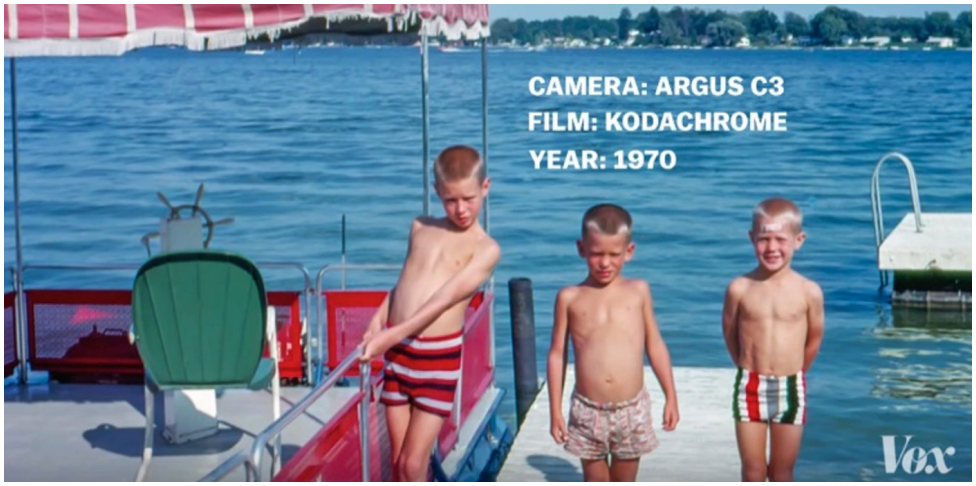
What are we teaching our models?

ML perpetuates stereotypes…



The choice of data defines decisions of ML model

Source: www.vox.com/2015/9/18/9348821/photography-race-bias



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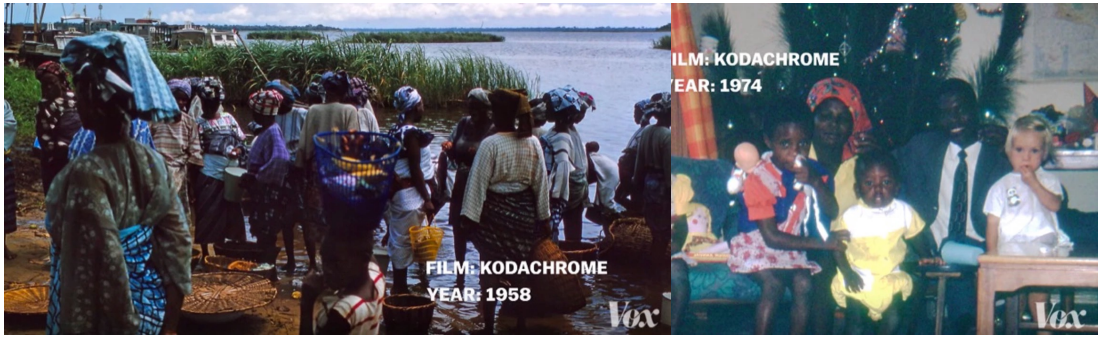

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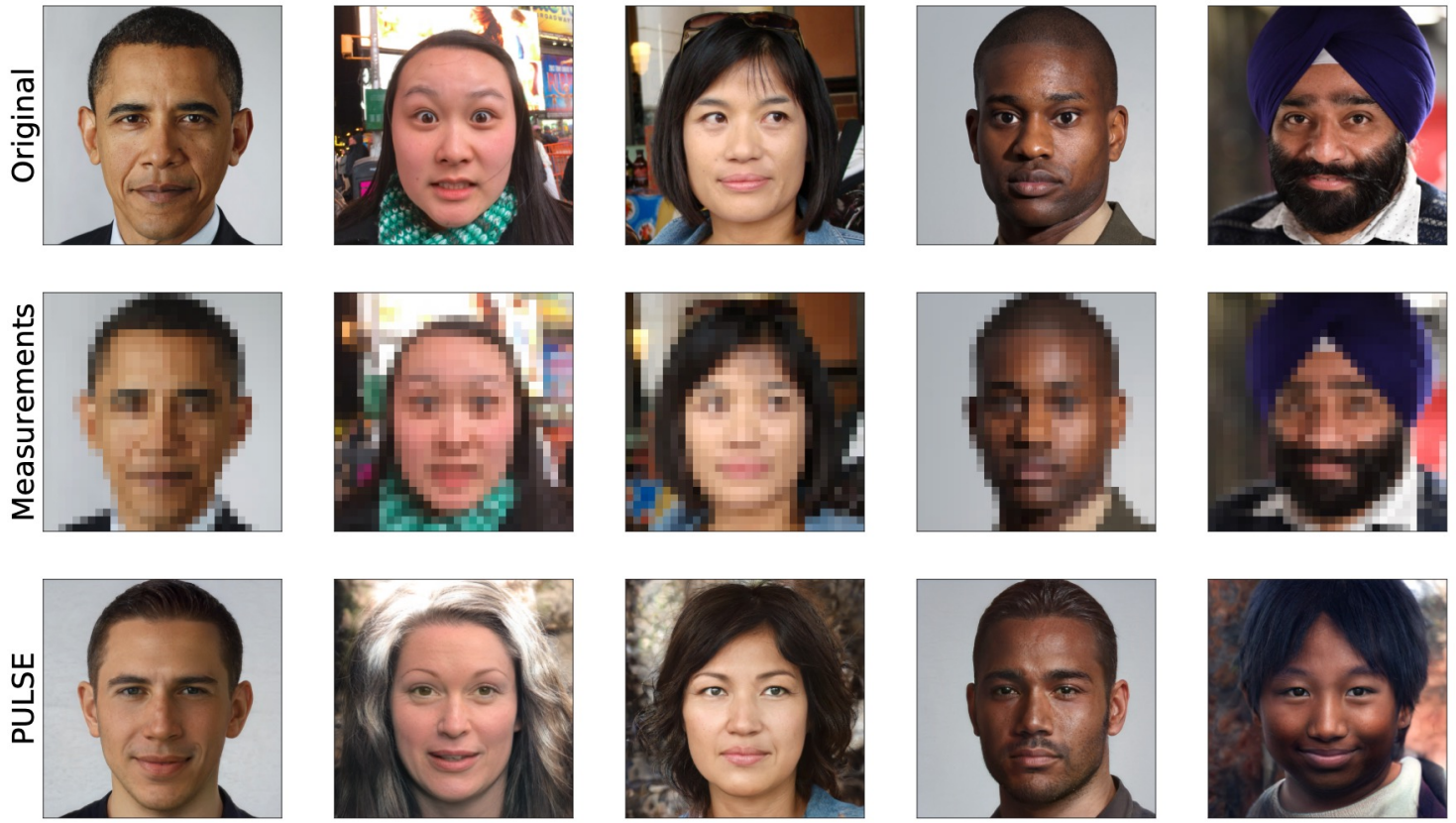
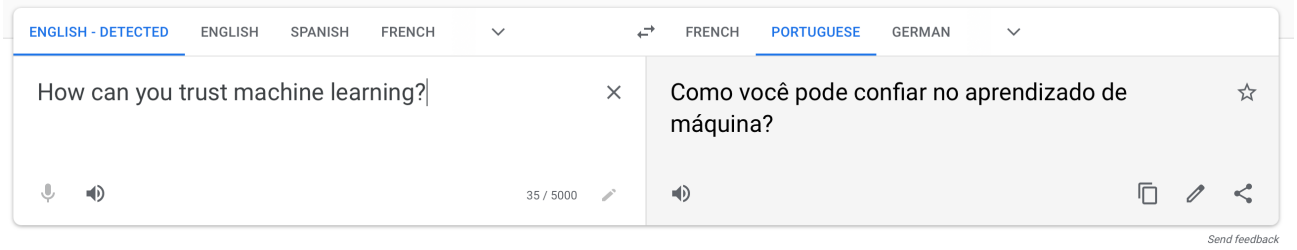
These biases show up in ML…



And, it's not just about diversity or coverage in the data we collect…

- Must ensure all development decisions reflect values we want the model to exhibit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How can you trust machine learning?
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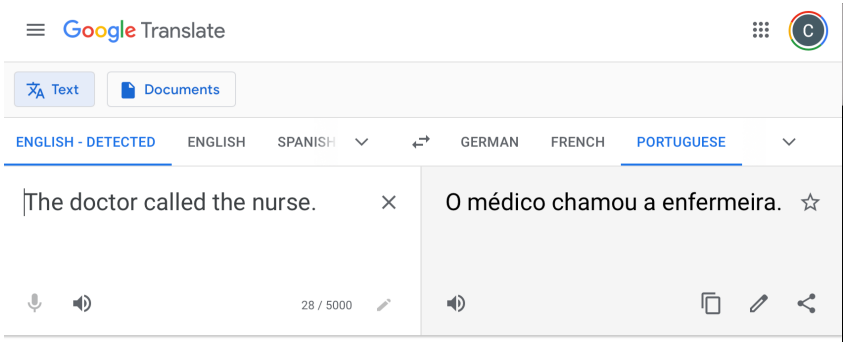
Como você pode confiar no aprendizado de máquina?
Send feedback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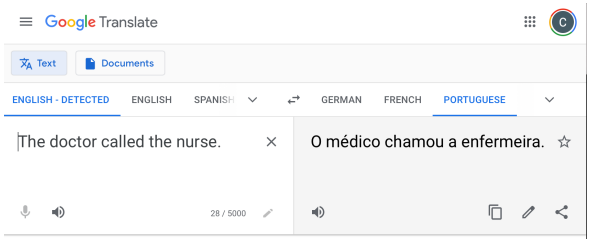

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all instances of “doctor” translated to male form

Even with infinite and representative data,
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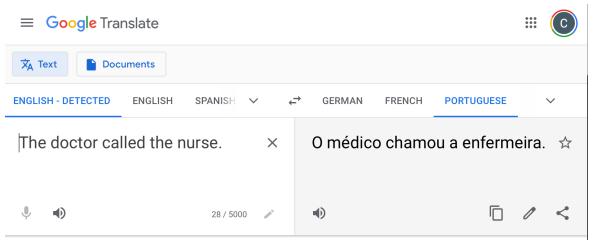

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Annotated fairness Slides

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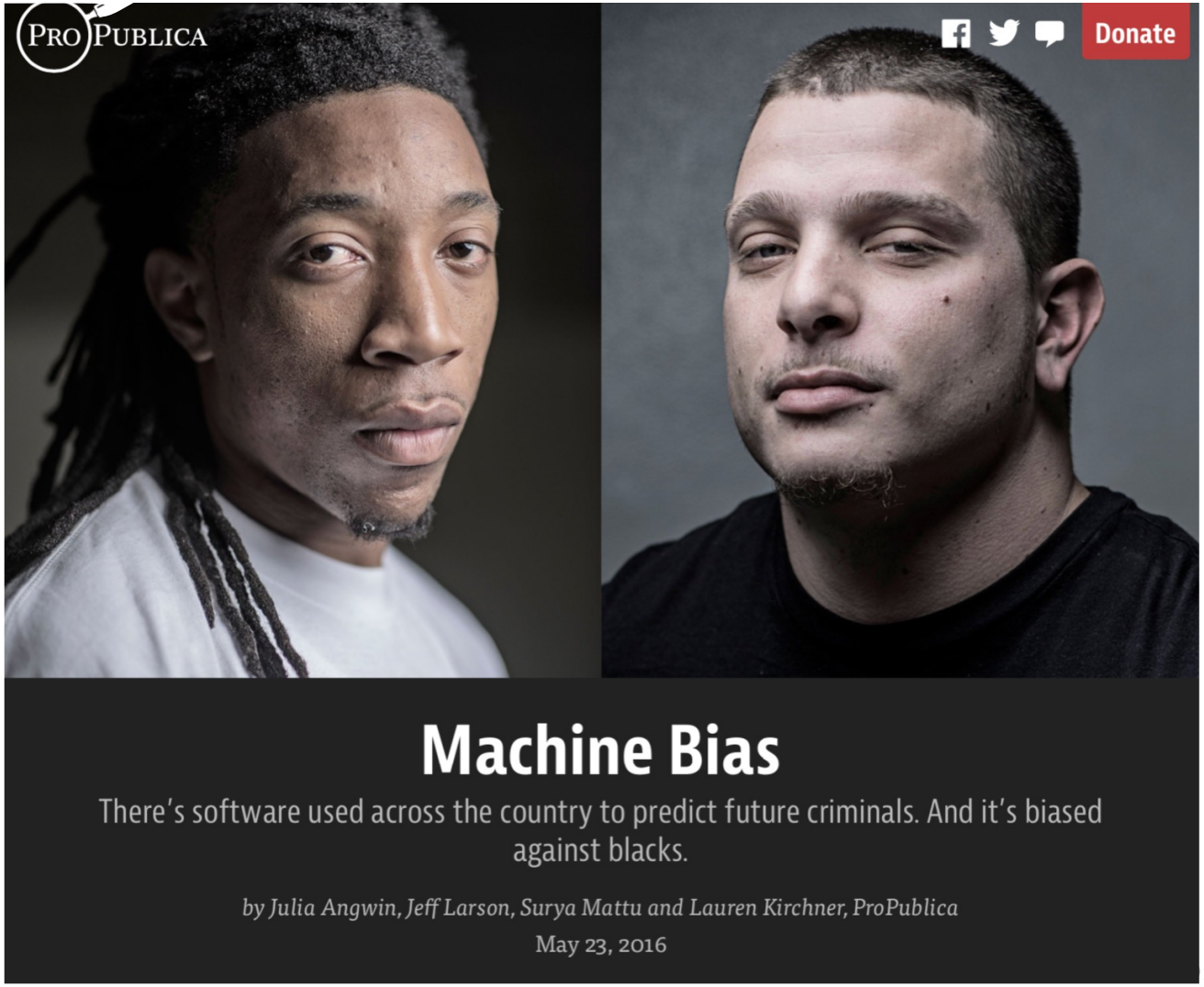
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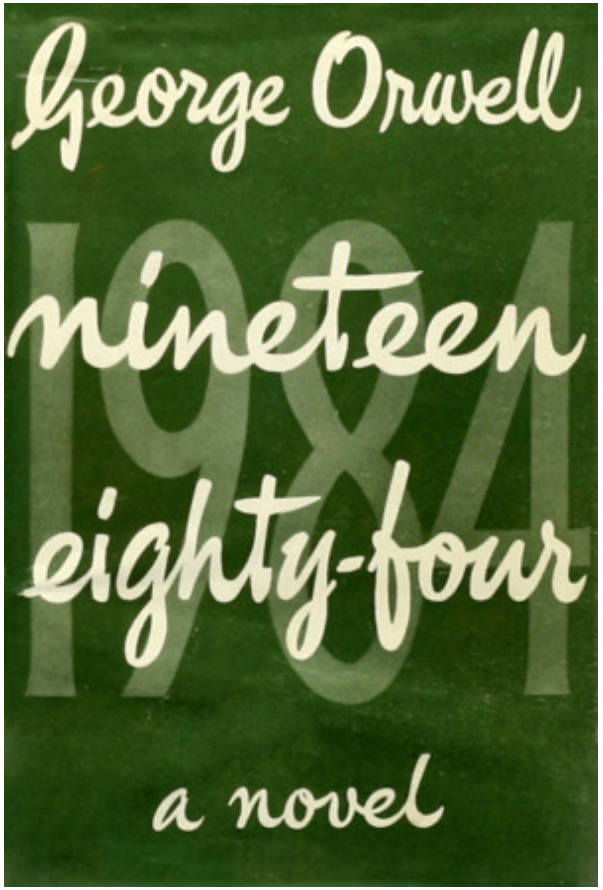

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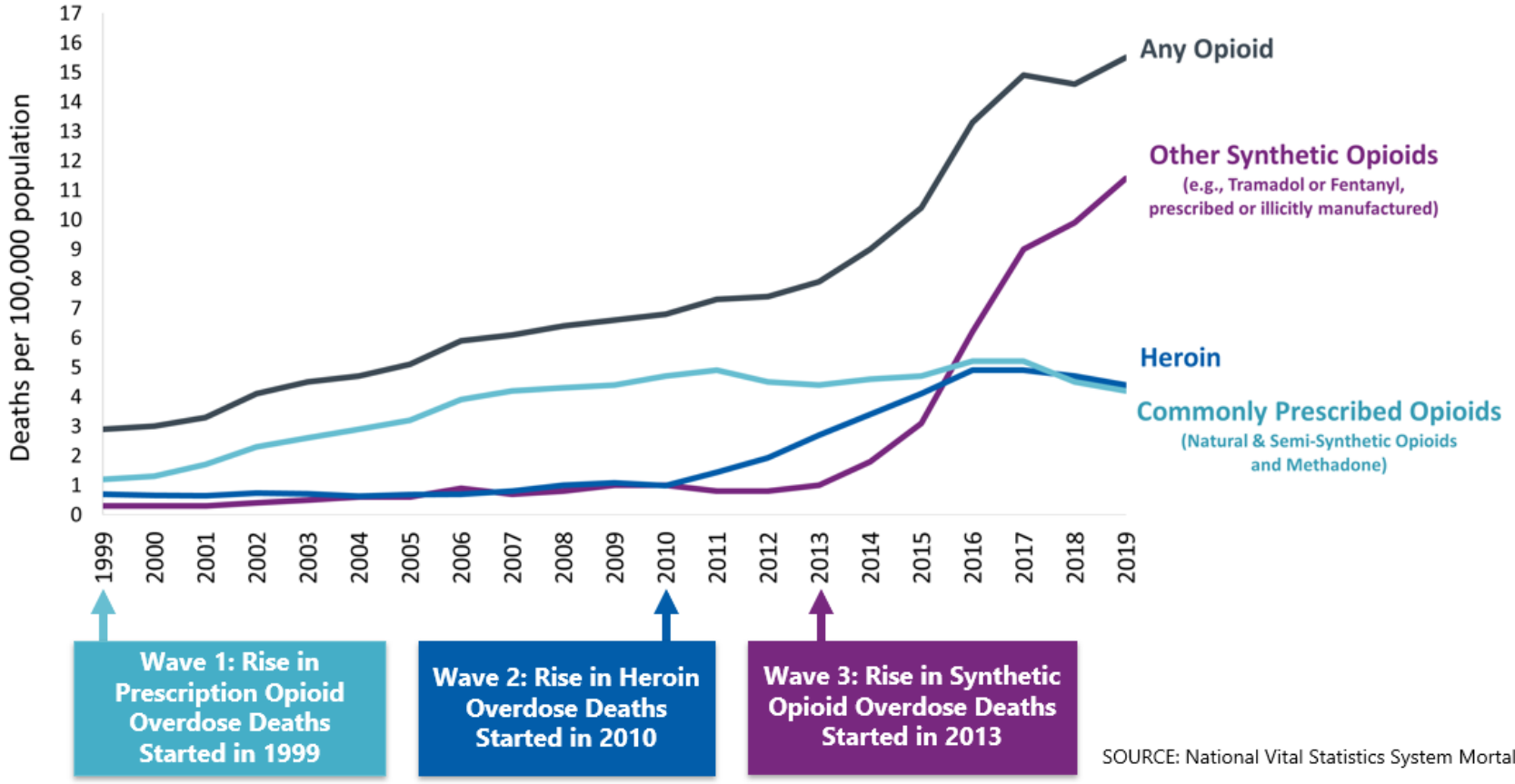

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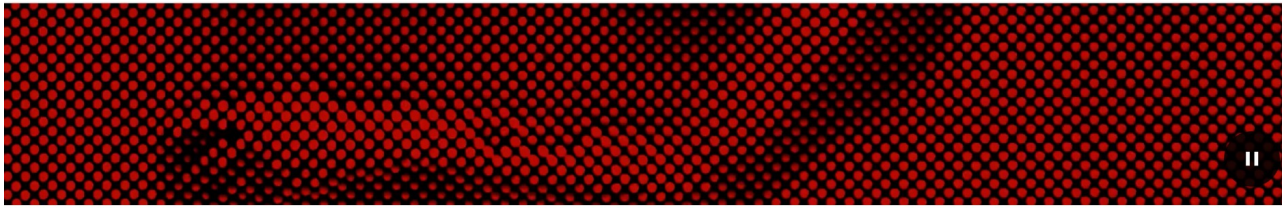

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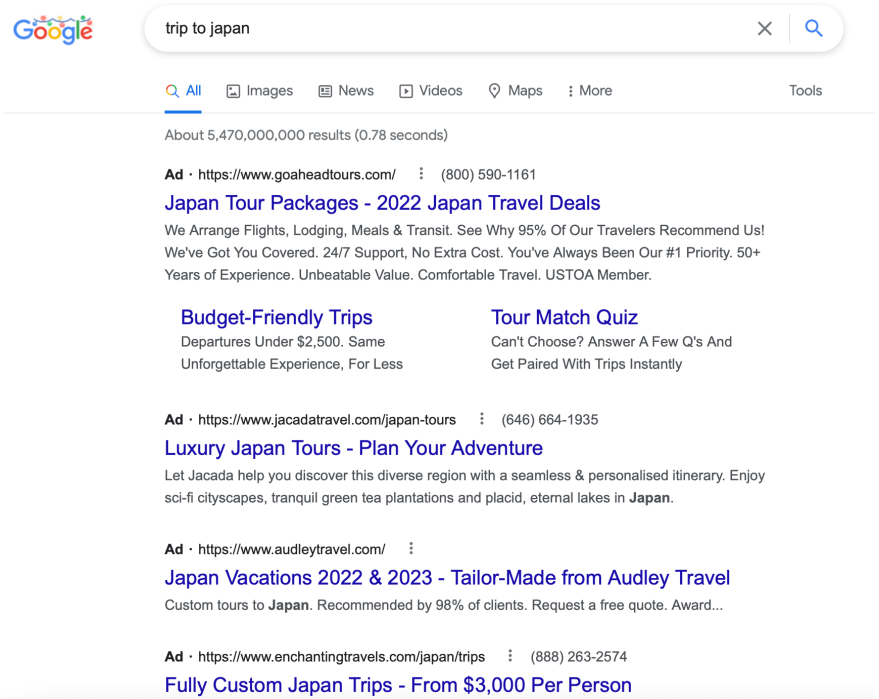

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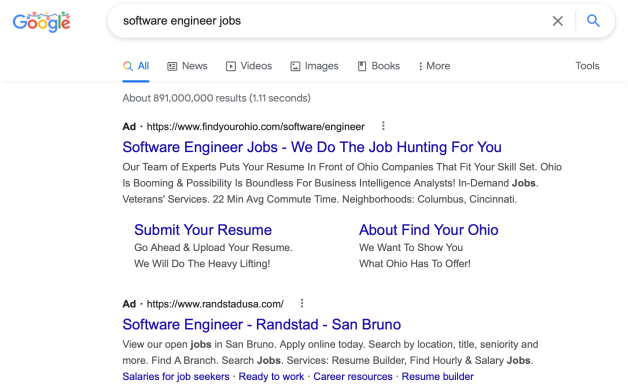

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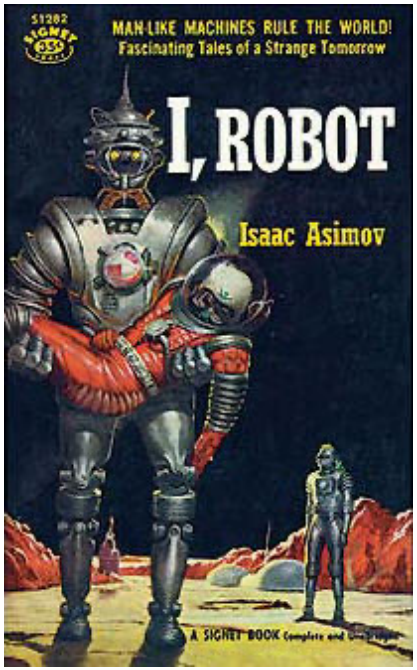

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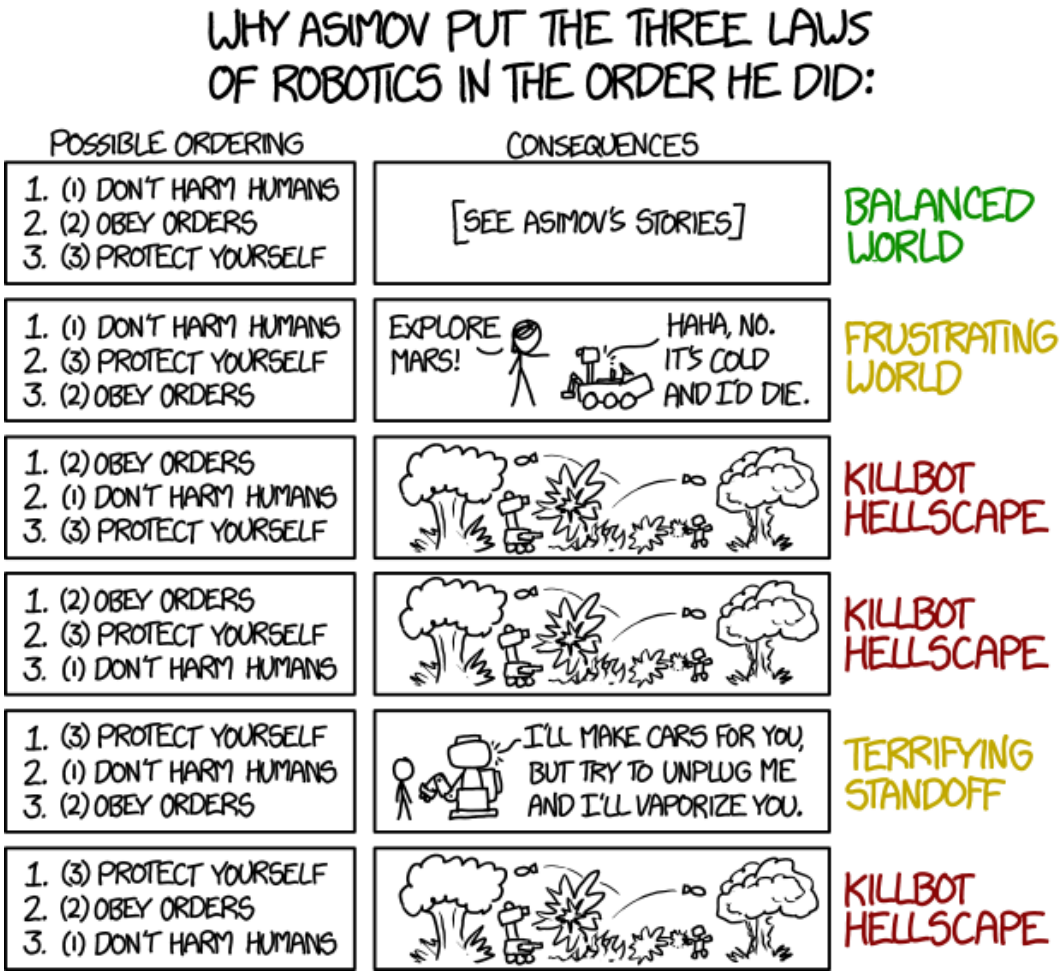

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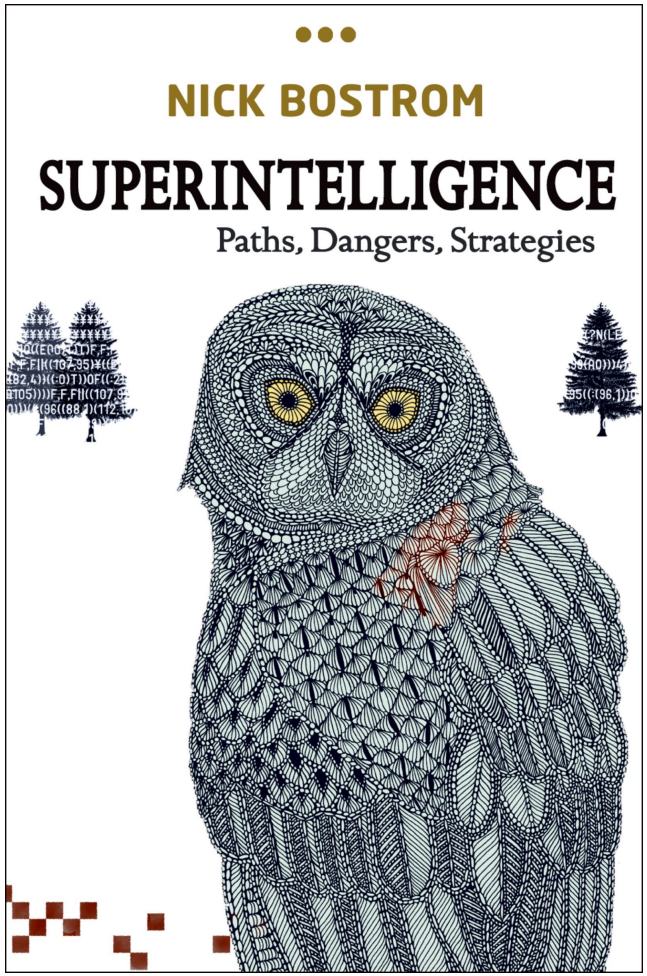

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- **'Public Accommodation'** (Civil Rights Act of 1964)

Legally-Recognized Protected Classes in the US

Race (Civil Rights Act of 1964); **Color** (Civil Rights Act of 1964); **Sex** (Equal Pay Act of 1963; Civil Rights Act of 1964); **Religion** (Civil Rights Act of 1964);**National origin** (Civil Rights Act of 1964); **Citizenship** (Immigration Reform and Control Act); **Age** (Age Discrimination in Employment Act of 1967);**Pregnancy** (Pregnancy Discrimination Act); **Familial status** (Civil Rights Act of 1968); **Disability status** (Rehabilitation Act of 1973; Americans with Disabilities Act of 1990); **Veteran status** (Vietnam Era Veterans' Readjustment Assistance Act of 1974; Uniformed Services Employment and Reemployment Rights Act); **Genetic information** (Genetic Information Nondiscrimination Act)

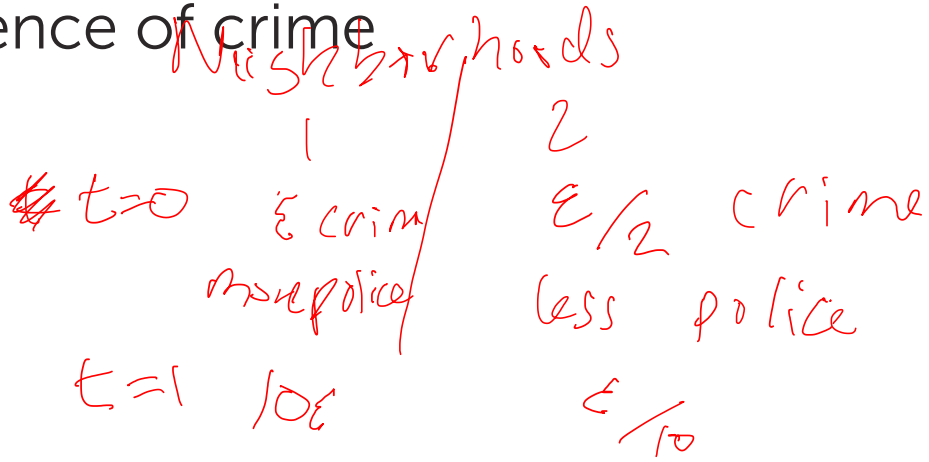
Sources of Bias

Sources of Bias: Human Bias

- Data reflects human decisions and biases
- Example: ML for Hiring decisions
  - Data from previous hiring decisions perpetuates existing biases
  - Could reduce bias by measuring employee success
    - Harder to measure and institutional biases can impact success

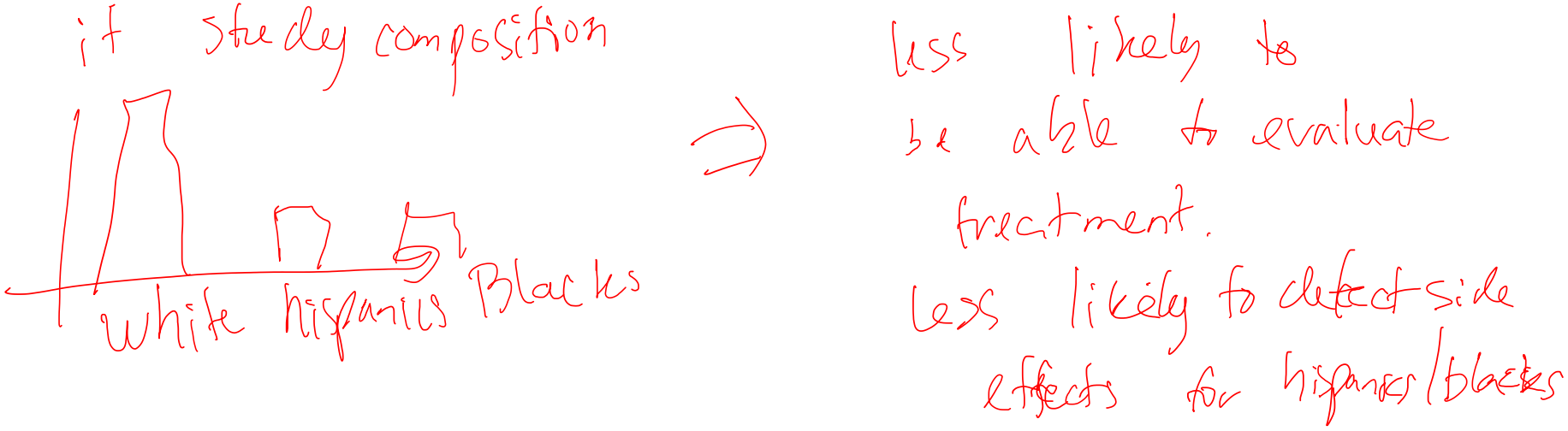
Sources of Bias: Negative Feedback Loops

- Data collected in biased fashion
  - Negative feedback loop: future observations confirm predictions and reduce further contradicting evidence
- Example: Allocation of police attention based on prevalence of crime



Sources of Bias: Sample Size Disparity

- Models for minority group may be less accurate, if less data is used
- Example: Race representation in medical studies



Sources of Bias: Unreliable Data

- If data from minority groups is less reliable or less informative
  - Models may be less accurate for minority groups
  - (Beneficial) interventions may less available to minority groups
- Examples:
  - Inaccurate census in predominantly minority neighborhoods
  - Medical interventions with limited diagnostic tools

Sources of Bias: Proxies

- Even if sensitive attributes (e.g., gender or race) are not used by model, there may be other proxy features that are correlated with sensitive attributes
- Example: Redlining in loan and insurance applications
  - https://www.npr.org/sections/thetwo-way/2016/10/19/498536077/interactive-redlining-map-zooms-in-on-americas-history-of-discrimination
  - https://www.npr.org/2017/05/03/526655831/a-forgotten-history-of-how-the-u-s-government-segregated-america

Mitigating Bias at Every Stage

- Problem definition
- Data collection
- Model development
- Model evaluation
- Use of predictions in practice
- Feedback loops

many ML papers only focus here

How do we measure fairness?

Consider a loan application…

- x – features of applicant (address, credit history,…)
- c – sensitive features of applicant (gender, race,…)
- d – decision (loan approved or denied) $d(x,c) \in \{0,1\}$
- y – (hidden) true target in decision (will this person pay the loan)

- Shorthand probability notation: $P(y|x,c) = P_c(y|x)$
- "Perfect" predictor: $d = y$

Fairness through Unawareness

- Definition: ignore sensitive features

$$d(x, c) = d(x)$$

- Desirable properties: Intuitive, Simple, some legal support.
- Criticisms: Proxies!!

x is correlated with c, e.g., Zipcode & race

Three Important Fairness Criteria

- Independence
- Separation
- Sufficiency

All these criteria are achievable…

- Techniques include:
  - Pre-processing
  - Changing training procedure
  - Post-processing

e.g., discussed in CS281

1. Independence

- Definition: Decision d independent of sensitive features **c**

$d \perp c \Rightarrow \forall i,j \quad P_{c=i}(d=1) = P_{c=j}(d=1)$

- A.k.a. **demographic parity**: Probability of loan approved is the same across sensitive attributes

$P_{Black}(\text{loan yes}) = P_{White}(\text{loan yes})$

Note: fraction of applicants need not be ~~close~~ the same for all races.

$P(c=White) \neq P(c=Black)$

Independence: Desirable Properties

- Simple
- Some legal support
- In some settings, can increase representation, e.g., in admissions

Independence: Shortcomings

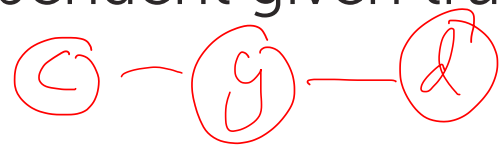
- Ignores possible correlations between y and **c**
  - Precludes perfect predictor d=y

- Laziness: quality of decision doesn't need to be uniformly good between groups

2. Separation

$d \perp c \mid y$

- Definition: decision d and sensitive features **c** conditionally independent given true target y



$\forall c, y \; \forall i, j \quad P_{c=i}(d \mid y) = P_{c=j}(d \mid y)$

Variant of Separation: False negative rate parity

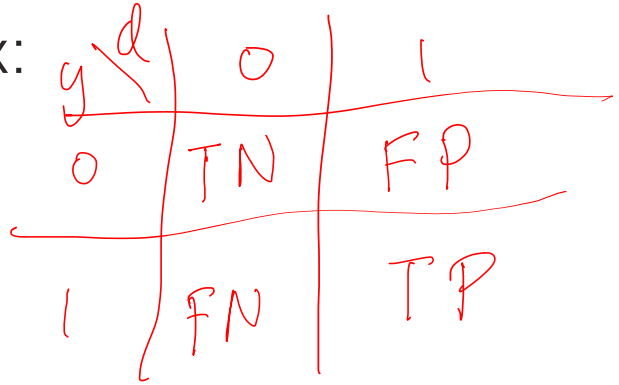
- Probability of loan denied for a deserving applicant is the same across sensitive attributes

FNR $P(d=0 \mid y=1)$

FNP Parity $\forall i,j \; P_{c=i}(d=0 \mid y=1) = P_{c=j}(d=0 \mid y=1)$

Separation: Confusion Matrix Interpretation (Equalized Odds, Equal Opportunity)

- Separation: $P_{c=i}(d|y) = P_{c=j}(d|y)$
- Confusion matrix:



all entries same for all groups

- Variants:

FNR parity, FPR parity

Equal opportunity: TPR parity $P_{c=i}(d=1|y=1) = P_{c=j}(d=1|y=1)$

Separation: Desirable Properties

- Optimality compatibility

$d = 5$ is allowed

- Incentivize to reduce errors equally across groups

Separation: Shortcomings

- Can amplify disparities

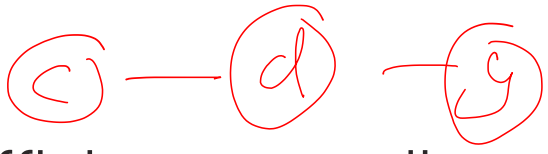
	C=0	C=1
Num candidates	100	100
Num qualified $y=1$	58	2

if 30 slots, equal opportunity: ⇒ 29 from C=0, 1 from C=1

if job is well paid, more children from C=0 will have access to better education, even more qualified candidates from C=0

3. Sufficiency

$y \perp c \mid d$



- Definition: decision variable d is sufficient to predict target y, independently of sensitive features **c**

$\forall y, d \quad \forall i, j \quad P_{c=i}(y \mid d) = P_{c=j}(y \mid d)$

- Equivalently, predictive rate parity:
  - Positive predictive rate:

$$P_{c=i}(y=1 \mid d=1) = P_{c=j}(y=1 \mid d=1)$$

  - Negative predictive rate:

$$P_{c=i}(y=0 \mid d=0) = P_{c=j}(y=0 \mid d=0)$$

decision d is consistent with goals of employer/bank

Sufficiency: Desirable Properties

- Optimality compatibility:

$d = 5$ is allowed

- Equal chance of success, given acceptance:

$$P_{Black}(y=1 \mid d=1) = P_{White}(y=1 \mid d=1)$$

Sufficiency: Shortcomings

- Also can amplify disparities

Same example as separation

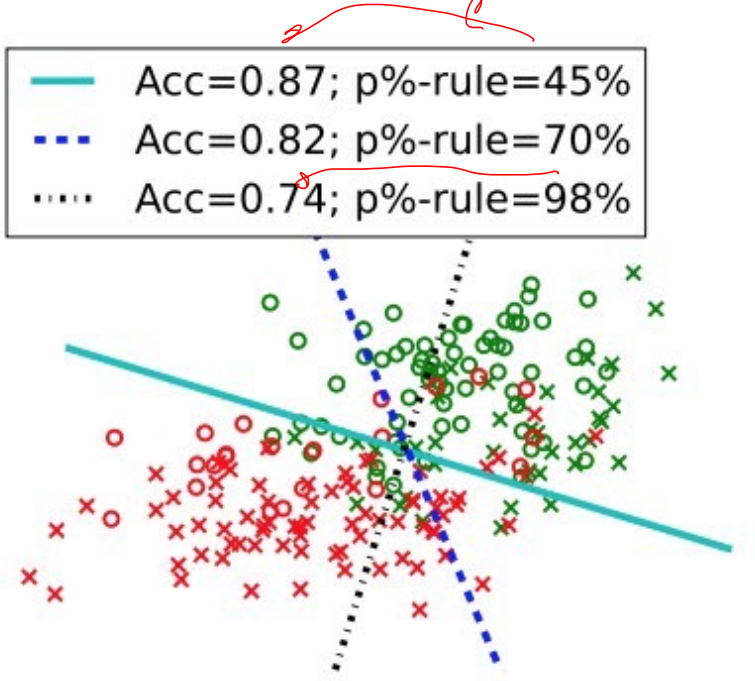
All these criteria are achievable…

- Techniques include:
  - Pre-processing
  - Changing training procedure
  - Post-processing

Trade-offs are Inevitable

Tradeoff Between Fairness and Accuracy

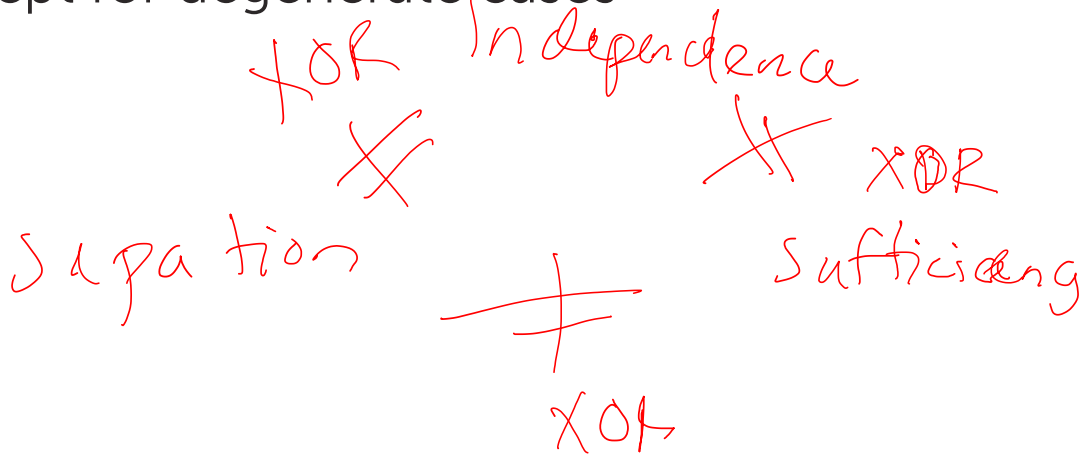
Tradeoff Between Group-Specific Performance and Average-Case Performance



Accuracy vs demographic parity [Zafar et al. AISTATS2017]

Impossibility Result

- Independence, Separation & Sufficiency are reasonable criteria
- **Theorem**: Any two of these is mutually exclusive!!
  - Except for degenerate cases



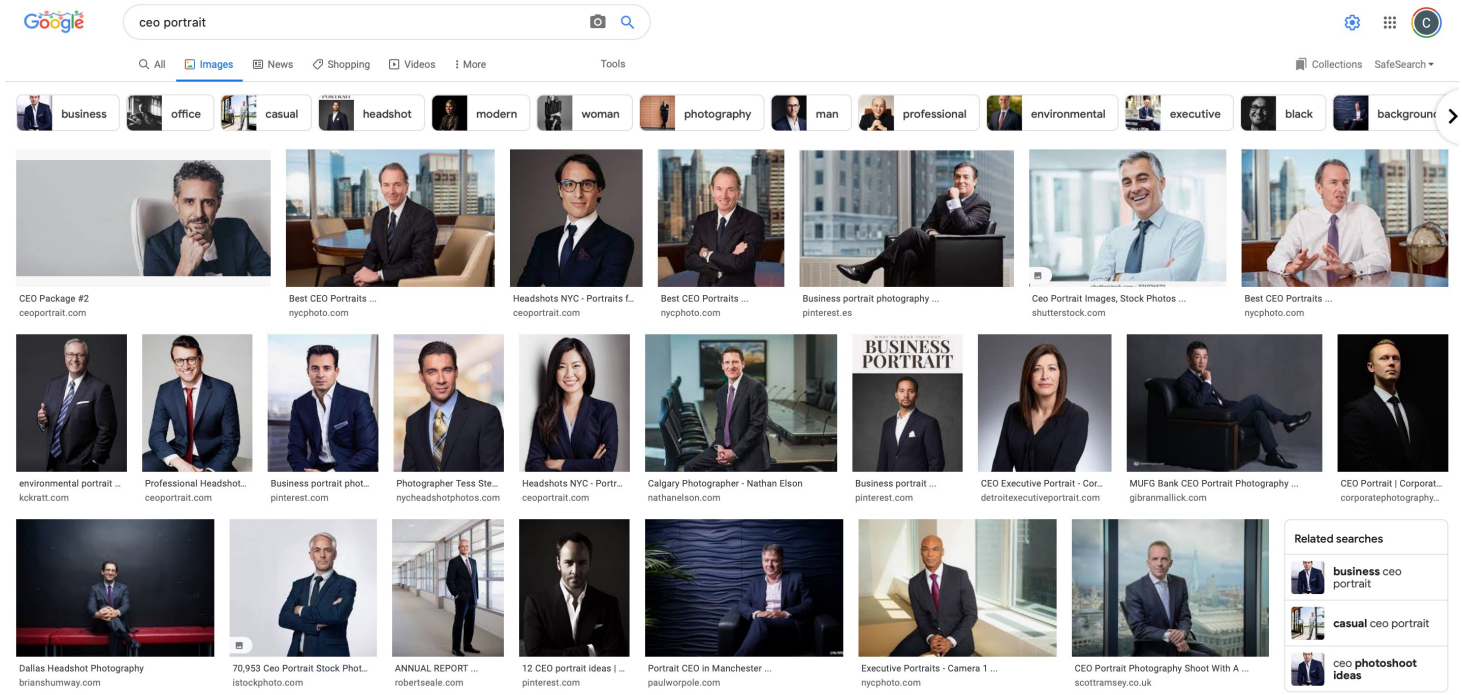
Trade-offs are necessary!

- Choose a criteria, instead of others?
  - Which one?
- Choose a balance between criteria?

- Very general issue in fairness and ML

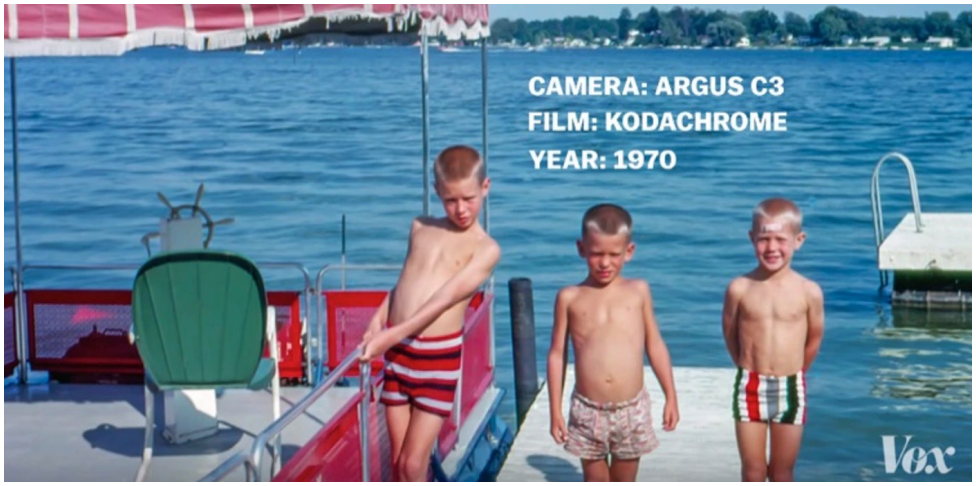
What are we teaching our models?

ML perpetuates stereotypes…

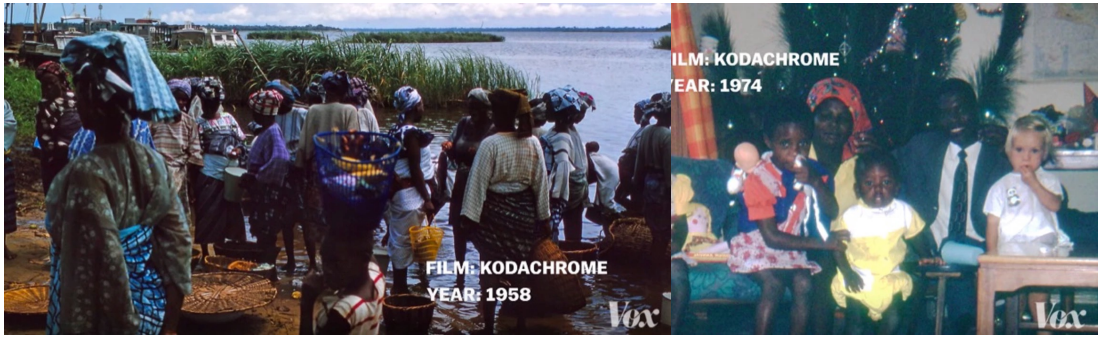


The choice of data defines decisions of ML model

Source: www.vox.com/2015/9/18/9348821/photography-race-bias



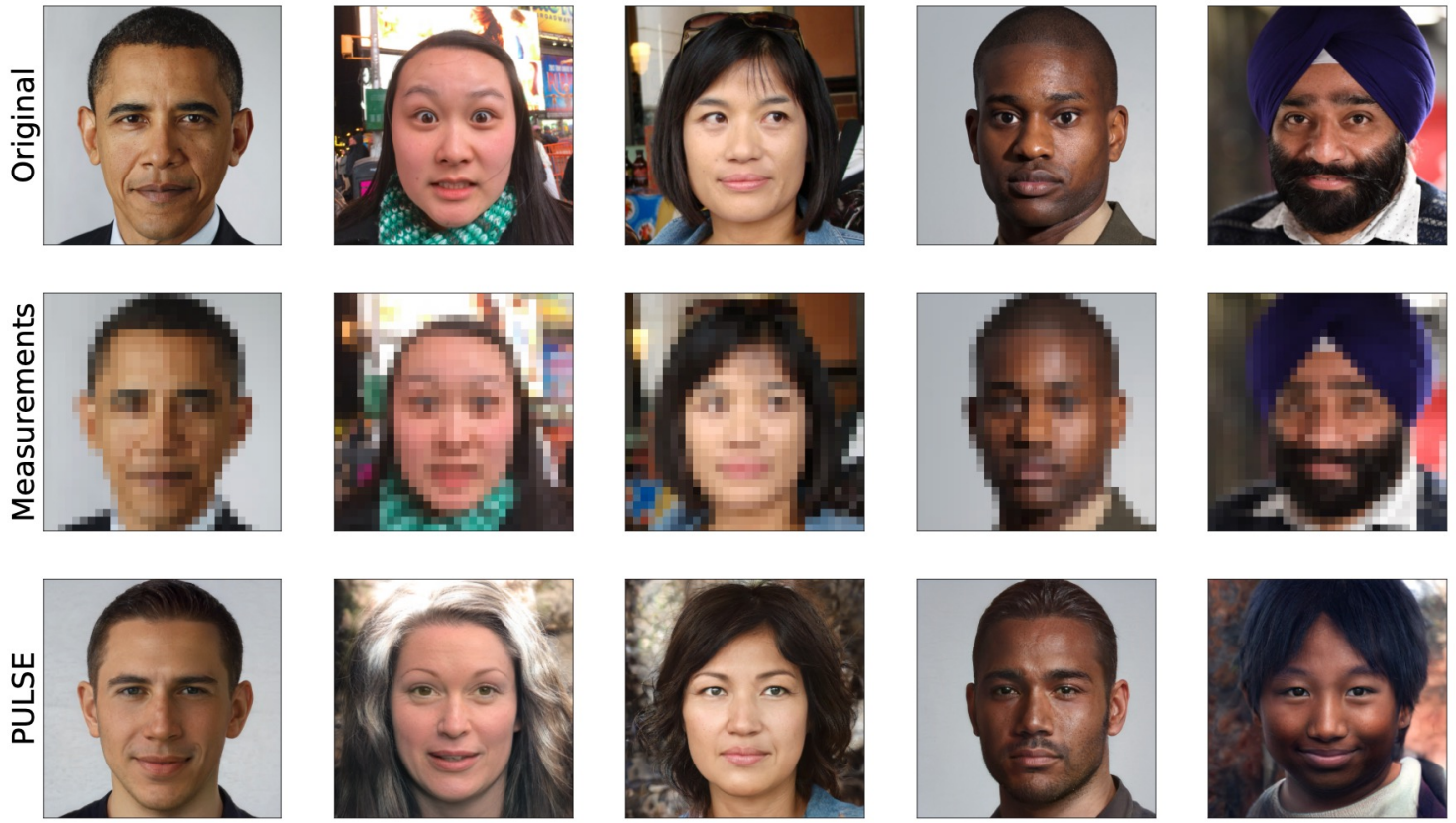
Source: www.vox.com/2015/9/18/9348821/photography-race-bias



Source: www.vox.com/2015/9/18/9348821/photography-race-bias

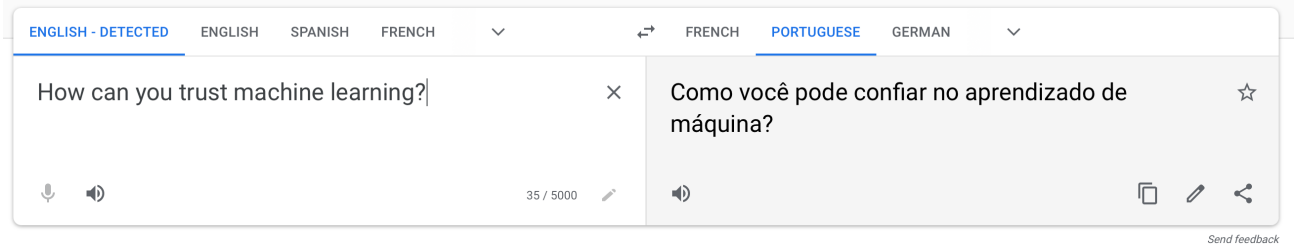
Source: www.vox.com/2015/9/18/9348821/photography-race-bias

These biases show up in ML…



And, it's not just about diversity or coverage in the data we collect…

- Must ensure all development decisions reflect values we want the model to exhibit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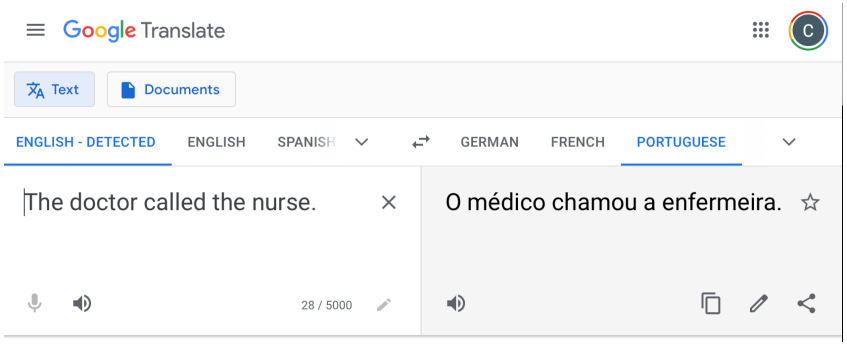
How can you trust machine learning?
35 / 5000
Como você pode confiar no aprendizado de máquina?
Send feedback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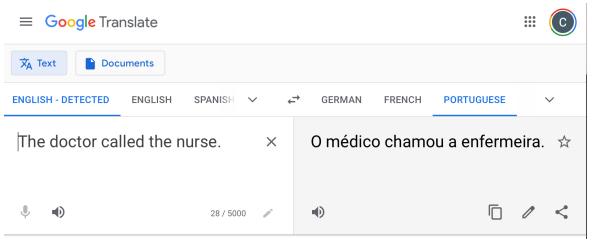
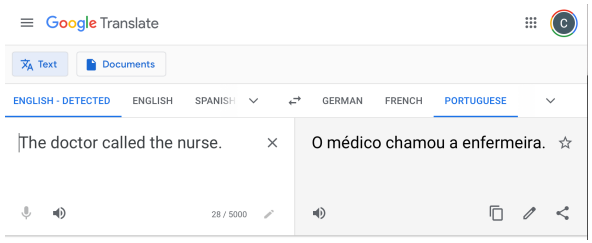
The doctor called the nurse.
O médico chamou a enfermeira.
28 / 5000



If >50% of doctors are male in the dataset,
all instances of “doctor” translated to male form

Even with infinite and representative data,
this issue will not be resolved



If >50% of doctors are male in the dataset,
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Even with infinite and representative data,
this issue will not be resolved

AI Ethics is about considering the consequences of every decision we make in the ML system